AN INTELLIGENT PATTERN RECOGNITION SYSTEM BASED ON NEURAL NETWORK AND WAVELET DECOMPOSITION FOR INTERPRETATION OF HEART SOUNDS

I. TURKOGLU[1], A. ARSLAN[2]
[1]Firat University, Technical Education Faculty, Electronics and Computer Dept.,
[2]Firat University, Engineering Faculty, Computer Dept. 23119, Elazig, Turkey

Abstract-**In this study, we develop a new automated pattern recognition system for interpretation of heart sound based on wavelet decomposition of signals and classification using neural network. Inputs to the system are the heart sound signals acquired by a stethoscope in a noiseless environment. We generate features for the objective concise representation of heart sound signals by means of wavelet decomposition. Classification of the features is performed using a back propagation neural network with adaptive learning rate. With two hundred record windows obtained from young humans are studied. One hundred of the record windows in database are selected for use as training phase for neural network. In the test result of the intelligent pattern recognition system with ten different types heart sound signals are acquired a high success.**
Keywords- **Heart sounds, Phonocardiogram, Wavelet decomposition, Neural networks, Pattern recognition.**

I. INTRODUCTION

Studies showed that the most of human deaths in the world are due to heart diseases. For this reason, early detection of heart diseases is one of the most important medical research areas [1]. The auscultation of the human heart sound is still one of the standard procedures used by physicians. The specific heart sound patterns can be easily listened by a stethoscope. Today the stethoscope is still well established, the phonocardiogram (PCG), reveals full information on diseases of cardiac valves, valvular defect, heart insufficiencies and heart throb [2]. Many attempts have been undertaken to automatically classify those signals using pattern recognition [3]-[7]. Automatic classification using advanced pattern recognition methods so far has been applied partly to heart sound [8]-[12].

This investigation is performed by use of eleven recognition features extracted from the wavelet decomposition of ten various heart sounds (Table I). Results showed that the correct classification rate of the neural network classifier is 98.5% (Table II).

The intelligent pattern recognition system used in the present study is include following units:

A. Pattern Recognition System

Pattern recognition is a system, which considers the various features of an input to match the input to the nearest output class. That is to say, the recognition process is the classification of the patterns [13].

A popular schematic of the pattern recognition process is shown in Figure 1 [14]. The sensors measure some physical process, which may be in one of many possible states of nature at a given time. The following block performs the important task of dimensionality reduction in one of two possible ways, depending on the application. Extraction involves a mathematical mapping from all the available measurements to a lower dimension feature space. On the other hand, selection entails choosing features among available measurements, without any functional mapping. Those measurements with discriminatory information are retained and those with redundant or irrelevant information are discarded. Finally, the role of classifier is to categorize the features of the recorded pattern into the appropriate class. The focus of work is on the classifier unit [15].

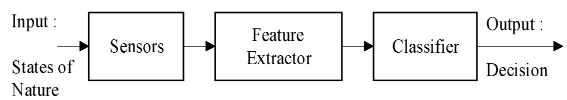

Fig. 1. A pattern recognition system.

B. Wavelet Decomposition

Wavelet transforms are rapidly surfacing in fields as diverse as telecommunications and biology. Because of their suitability for analysing non-stationary signals, they have become a powerful alternative to Fourier methods in many medical applications, where such signals abound [16]-[18].

Wavelet decomposition uses the fact that it is possible to resolve high frequency components within a small time window, and only low frequencies components need large time windows. This is because a low frequency component completes a cycle in a large time interval whereas a high frequency component completes a cycle in a much shorter interval. Therefore, slow varying components can only be identified over long time intervals but fast varying components can be identified over short time intervals.

Wavelet decomposition can be regarded as a continuous time wavelet decomposition sampled at different frequencies at every level or stage. The wavelet decomposition function at level m and time location t_m can be expressed as Equation (1):

$$d_m(t_m) = x(t) * \Psi_m\left(\frac{t - t_m}{2^m}\right) \tag{1}$$

Where Ψ_m is the decomposition filter at frequency level m. The effect of the decomposition filter is scaled by the factor 2^m at stage m, but otherwise the shape is the same at all

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Abstract

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stages. This wavelet decomposition function is sampled at different rates at every stage to produce the wavelet decomposition coefficients. The sampling rate at stage m output is $F_s/2^m$. The level m coefficients are denoted as $d_m[k_m]$, where k_m is an integer such that $k_m=t/\Delta t_m$. The synthesis of the signal from its time-frequency coefficients given in Equation (2) can be rewritten to express the composition of the signal x[n] from its wavelet coefficients.

$$\begin{aligned} d[n] &= x[n] * h[n] \\ c[n] &= x[n] * g[n] \end{aligned} \tag{2}$$

where h[n] is the impulse response of the high pass filter and g[n] is the impulse response of the low pass filter [19].

C. Neural Networks

Artificial neural networks are systems that are deliberately constructed to make use of some organizational principles resembling those of the human brain. They represent the promising new generation of information processing systems. Neural Networks are good at tasks such as pattern matching and classification, function approximation, optimisation and data clustering, while traditional computers, because of their architecture, are inefficient at these tasks, especially pattern-matching tasks [20].

A neural network is a parallel-distributed information processing structure with the following characteristics:

- It is neurally inspired mathematical model.
- It consists of a large number of highly interconnected processing elements.
- Its connections hold the knowledge.
- A processing element can dynamically respond to its input stimulus, and the response completely depends on its local information.
- It has the ability to learn, recall, and generalize from training data by assigning or adjusting the connection weights.
- Its collective behaviour demonstrates the computational power, and no single neuron carries specific information.

Because of these characteristics, neural networks are commonly used in the large area [21].

II. METHODOLOGY

Figure 2 shows the automated identification system we developed. It consists of three parts: a) Data acquisition and preprocessing, b) Feature Extraction, c) Classification.

A. Data Acquisition and Preprocessing

Heart sounds are sampled at 44.1 Khz using MATLAB software. Analog to digital conversion resolution is 16 bits. Type and average period of each other of these heart sounds are shown in Table I. Each heart sound is approximately assumed in general to have duration of 1.13 sec, and thus heart sounds are divided windows having 50,000 samples.

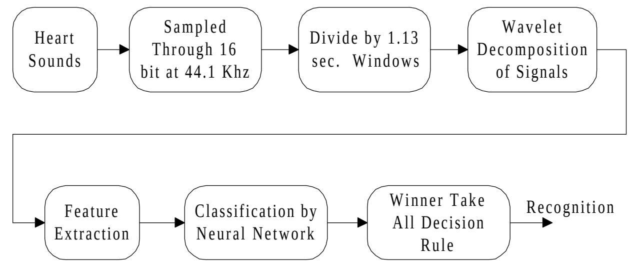

Fig. 2. Block diagram of the heart sound identification system.

TABLE I
TYPE OF HEART SOUNDS

No.	Type	Auscultation area	APOW (sec)
1	Normal heart sound	Apex	1.13
2	S3	Apex	1.13
3	S4	Apex	0.9
4	Aortic stenosis	Right base	0.9
5	Mitral regurgitation	Apex	0.79
6	Midsystolic click	Apex	1.13
7	Ventricular septal defect	Lower left sternal border	0.9
8	Atrial septal defect	Left base	0.9
9	Mitral stenosis	Apex	1.13
10	Aortic regurgitation	Mid left sternal border (3rd intercostal space)	1.02

APOW: Average period of waveform

B. Feature Extraction Using Wavelet Decomposition

Feature extraction is the key to pattern recognition. The Figure 3 shows the feature extraction structure, which is performed using wavelet coefficients of the wavelet decomposition at ten levels. Wavelet decomposition is obtained using the Daubechies 4-coefficient wavelet filters [22]. For example, the wavelet decomposition at ten-levels of the aortic regurgitation signal in a window is shown in Figure 4.

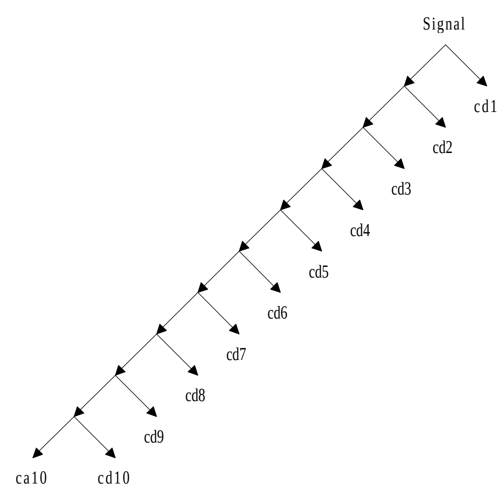

Fig.3. The wavelet coefficients of the wavelet decomposition at ten levels.

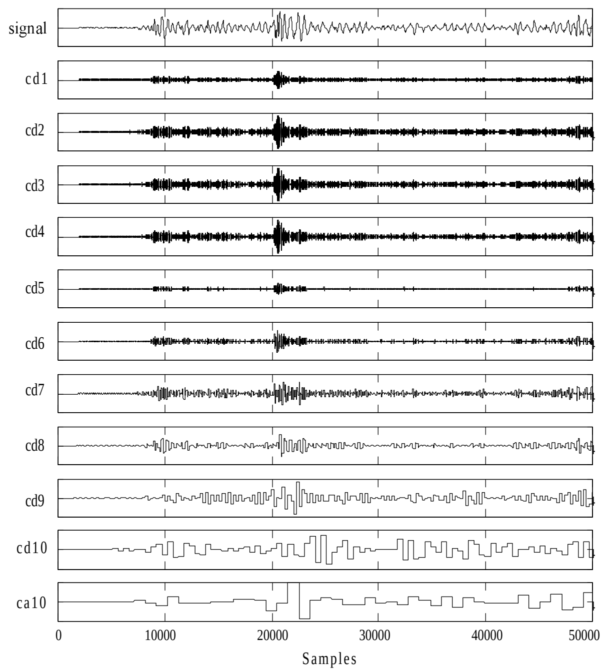

Fig.4. The wavelet decomposition at ten-level of the aortic regurgitation signal in a window.

The features are extracted from wavelet decomposition components of the signals using Equation (3). Thus, the each component of signal is expressed with a single value,

$$a_j = \frac{\sum_{i=1}^{n} \left| c_{ji} \right|}{n} \tag{3}$$

where a_J is the average of j^{th} component of signal and the c_{ji} indicates the j^{th} component vector of wavelet decomposition of signal. n is the dimension of the signal in a window. Exactly like this, the feature vector is defined the wavelet decomposition of the signal analysed at ten levels as follow:

$[cda_1, cda_2, cda_3, cda_4, cda_5, cda_6, cda_7, cda_8, cda_9, cda_{10}, caa_{10}]$

For each recording, these feature parameters are used providing an eleven-component feature vector as the input to the neural network classifier.

C. Classification by Adaptive Learning Backpropagation

Recent developments in the field of artificial neural networks have made them a powerful tool to pattern classifiers. The application of neural networks has opened a new area for solving problems irresolvable by other pattern classifying techniques. A number of neural network algorithms and their applications have been widely reported [23]. Among the many neural networks learning algorithm, the adaptive learning back propagation is considered the most useful learning algorithm.

The training characteristics and the structure of the neural network used in this study are as follow:

The Number of Layers: 3
The number of neuron on the layers: 11 - 15 -10
Adaptive learning rate: 0.005 (+1.04, -0.7)
Momentum coefficient: 0.98
Sum-squared error: 0.005
Activation Functions: Tangent Sigmoid

The winner-take-all decision rule used in this study means that the input pattern feature vector was be set to the class belonging to the neural network output node whose value is the biggest. In the training phase of neural network structure, the feature vectors of signal types shown in Figure 5 are used. The number of train samples is one hundred windows and ten windows are used for each heart sound sample.

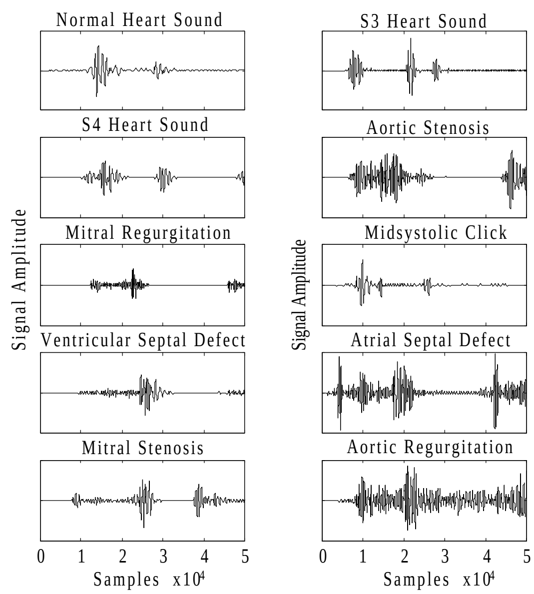

Fig. 5. The one-window samples of the signal types of heart sound.

D. Classification Results

Table II shows the classification results for each heart sound. Classification results of the test data set are given at correct form and incorrect form. The testing data set is used one hundred windows apart from training data set.

TABLE II
CLASSIFICATION RESULTS

Heart Sound Types	Correctly classified		Incorrectly classified	
	Number	ARP (%)	Number	ARP (%)
Normal heart sound	9	98	1	92
S3	10	99	--	--
S4	9	99	1	99
Aortic stenosis	10	99	--	--
Mitral regurgitation	10	99	--	--
Midsystolic click	10	99	--	--
Ventricular septal defect	9	99	1	92
Atrial septal defect	9	95	1	99
Mitral stenosis	10	99	--	--
Aortic regurgitation	10	99	--	--
Total	96	98.5	4	95.5

ARP: The Average Recognised Percent.

III.DISCUSSION AND CONCLUSION

The feature vectors obtained by the developed method were used as the input to neural network classifier. The classifier consists of feed forward neural network using back propagation learning rule of adaptive learning rate to train the network. In this study, ten varieties of heart sounds were used on the contrary to the previous studies. The training set, which included one hundred data samples are used to train the network and the testing set, which included one hundred data samples apart from training set are used to check the automatic pattern recognition performance. The best of these recognition results were obtained a 99% correct recognition rate. This recognition rate indicates the robustness of the developed feature extraction method by us. However, there are 4% incorrect classifications. The misclassification percent might reduce with a larger train set. Our further work will continue in this direction.

The most important aspect of the intelligent pattern recognition system is the ability of self-organization of the neural network without requirements of programming and the immediate response of a trained net during real-time applications. These features make the intelligent pattern recognition system suitable for automatic classification in many acoustical signal applications like interpretation of heart sound. These results point out to the ability of design of a new intelligence medical assistance system.

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